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Measuring emission-reduction and energy-conservation efficiency of Chinese cities considering management and technology heterogeneity

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ABSTRACT

In response to global climate change and greenhouse gas emissions, China not only is under enormous pressure to reduce emissions from all over the world, but also confronts the problem of domestic energy shortage and ecological environment deterioration. Compared with other developed countries and regions, China has implemented an extensive development model over a long period, consuming large amounts of resources and sacrificing the environment. Therefore, how to reduce emissions and conserve energy is essential for the rapid development of China. To deal with this issue, this paper proposes the improved DEA models for measuring emission-reduction and energy-conservation (EREC) efficiency. Compared with other DEA models, the models in this paper consider not only the heterogeneity of energy management in varied regions, but also the technology gap between regions. In order to assess the level of technological development in different regions, this paper proposes a new technology gap ratio index (TGR). The proposed approach is applied for measuring the EREC efficiency of 211 Chinese cities. The results show that the overall EREC efficiency of Chinese cities is low, and the central area has the lowest EREC efficiency. There is significant technology gap between the regions; the technology level is the highest in the eastern region but the lowest in the northeastern region. We also reveal that managerial and technical factors are the two main sources for the loss of EREC efficiency in Chinese cities. The specific strategies of management and technology are suggested for all cities in different areas.
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1. Introduction

In 2010, following decades of improvement, China's economic development attained considerable achievements to become the second-largest economy in the world (Lee, 2014; Bi et al., 2015). However, simultaneous with this great economic achievement, China is confronting issues of environmental pollution and resource shortage (Ji et al., 2017a; Song et al., 2015). Decision makers in the Chinese government generally set targets to reduce emission and conserve energy (Ji et al., 2017b). The strategies to achieve these targets are implemented at the city level. As the major contributors to economic development, Chinese cities consume vast quantities of resources and energy as well as emit large volumes of pollutants. Emission of these pollutants contributes to serious ambient air pollution (Ji et al., 2017c). A typical example refers to one pollution-driven event that occurred in the winter of 2016, when hazy and overcast weather affected over 17 provinces in China and covered approximately 1,420,000 square kilometers. This event confirmed further that energy waste and pollution emissions from cities must be alleviated by implementing emission-reduction and energy-conservation (EREC) policies stringently.

Existing literature on EREC research is rooted in measuring and improving environment or energy utilization efficiency. Hu and Wang (2006) proposed a data envelopment analysis (DEA) model to assess energy utilization efficiency. Since then, many subsequent researchers have used varied DEA models to evaluate the energy utilization efficiency. For instance, Shi et al. (2010) utilized DEA models to estimate Chinese energy utilization

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efficiency at the provincial level and analyzed the energy-saving potential of these provinces. Zhang et al. (2011) integrated a total-factor index into a DEA method to assess the energy utilization efficiency of developing countries using data from 1980 to 2005. From the perspective of environmental efficiency, Zhang et al. (2008) utilized a DEA model to evaluate the environmental efficiency levels of Chinese industries. Zhou et al. (2008) used a DEA approach to assess and compare environmental efficiency among eight world areas. In order to extend the total-factor technique for energy or environment efficiency, Zhou et al. (2010) proposed the evaluation indexes for the total-factor carbon emission efficiency. Wang et al. (2013a) analyzed carbon emission performance in Chinese provinces from the perspectives of timing and spacing. Wu et al. (2014) took the output competition into account, and proposed a DEA model with fixed sum outputs for evaluating the environment performance of China's industry. In order to analyze the efficiency of economic, environment and energy (3 E), Wang and Feng (2015) developed a slack-based DEA model. In addition, they discussed the influence factors of 3 E efficiency change from 2002 to 2011 in terms of technology, production scale and management ability. Sueyoshi and Yuan (2015) applied DEA for assessing the environment performance through considering PM2.5 and PM10 as undesirable outputs. They concluded that the Chinese government should implement more stringent energy consumption control policies in the major cities, such as Beijing, Tianjin, Shanghai and Chongqing. Prior research focused individually on energy-saving efficiency or emission-reduction efficiency. Wu et al. (2015a, b) proposed a fuzzy DEA model incorporating Russell technique under the imprecise circumstance. Then the proposed model was applied for benchmarking the Chinese thermal power firms' efficiencies. For decreasing the energy consumption and accelerating the sustainable development, Li et al. (2017) empirically examined the relationships among energy consumption, behavioral intention, and situational factors. They concluded that situational factors have the most significant and effective effect on energy saving behavior. As for evaluating both emission-reduction and energy-conservation efficiency, few scholars have addressed this issue from a general city-level standard aspect (see, e.g., Wang and Wei, 2014; Zha et al., 2016; Guo et al., 2017). However, since a huge number of Chinese cities are widely scattered throughout the country, and industrial development among them is heterogeneous, applying a general city-level standard to evaluate and analyze energy-saving and emission-reduction programs in these cities is inappropriate. Thus, to formulate and implement effective policies, measuring emission-reduction and energy-conservation efficiency from the perspective of management and technology heterogeneity among cities is very necessary.

Considering management and technology heterogeneity, Wang et al. (2015a) further assessed both emission-reduction and energy-conservation efficiency from empirical analysis of Chinese cities, and concluded that high- and low-earning cities have higher EREC efficiency while the middle-earning cities have the lowest the EREC efficiency. However, these studies, including Wang et al. (2015a), assessed the EREC efficiency through the traditional or proposed models considering only a set of weights. This may overestimate EREC efficiency. Our paper differs from the above literature in not only incorporating management and technology heterogeneity, but also unifying the energy-saving and emission-reduction into a framework through a different weighting scheme to accurately evaluate EREC efficiency, which further extends the work of Kuosmanen (2005) and Wang et al. (2015a).

For methodologies of measuring efficiency, directional distance function (DDF) has been extensively employed to evaluate energy utilization or environment efficiency (Oh, 2010; Zhou et al., 2012; Sueyoshi and Goto, 2012). Compared with traditional DEA models, DDF can simultaneously increase desired outputs and reduce undesirable ones in the process of efficiency calculation. Owing to this characteristic, Färe et al. (2007) and Chiu et al. (2012) applied a DDF method to assess and compare the environment efficiency of coal-burning power plants from the United States and the countries of the Organization for Economic Co-operation and Development. Picazo et al. (2012) and Beltrán et al. (2014) proposed a new DDF that integrates the meta-frontier method to study the ecological efficiency of farmers in Spain. Conventional DDF models frequently adopt a radial measure (Färe et al., 2007; Ji et al., 2016), which reduces undesirable outputs and increases desirable ones in accordance with the same proportion. Nevertheless, this approach could not be normally applied in reality because undesirable and desirable outputs are difficult to change at the same rate. To solve this problem, Wang et al. (2013b) employed an improved DDF method from a non-radial angle to measure Chinese energy utilization efficiency. Zhang et al. (2014) assessed the CO_2 emission and energy utilization efficiency of Chinese power stations and analyzed the effect of scale on efficiency. Zhou et al. (2016) proposed a DEA-Malmquist method for analyzing efficiency changes in Chinese cities' energy utilization and pollutant reduction over time. The empirical results indicate that China's city efficiency growth rate is approximate 16% per year.

For the characteristics of DEA models considering undesirable outputs, most of the previous studies employed Shephard's approach (Shephard, 1970, 1974) to examine the tradeoffs between the desirable and the undesirable outputs. However, Kuosmanen (2005) argued that the Shephard approach would ignore the feasible DEA axioms of input-output vectors. These DEA models using the Shephard technology will lead to the overestimated efficiencies for the evaluated DMUs, even in the case of large samples. Besides, the benchmarks for inefficient DMUs trend to be technically inefficient (Kuosmanen and Matin, 2011). Kuosmanen and Podinovski (2009) also used a simple numerical case to validate that Shephard's technology are non-convex, and difficult to satisfy the key axioms of DEA. The subsequent study by Podinovski and Kuosmanen (2011) further pointed out that Shephard technology does not have a theoretical explanation if the convexity assumption is relaxed or only convexity of output sets is assumed.

The other characteristics of the previous studies can be summarized as follows. First, most of studies used the technology gap ratio (TGR) index to represent the technology heterogeneity between two different types of frontiers. Some scholars have used the non-radial DDF and the meta-frontier techniques to calculate the TGR. However, Wang et al. (2016) pointed out that the TGR may be greater than unity if non-radial DDF is incorporated into the meta-frontier technique. If there are a large number of samples to be evaluated, the TGR results may deviate from real values. Second, the above research focuses on EREC in the process of production. A comprehensive grasp of the overall picture of EREC is still relatively few (Zhou et al., 2016). Third, some studies provided a subjective preference for EREC index. Wang et al. (2015a) pointed out that heavily weighting EREC will fail to support the targeted policy development adequately.

Motivated by the aforementioned research gaps, this paper will evaluate the cities' EREC performance by considering management and technology heterogeneity. Particularly, this paper aims to answer the following questions: (1) How to model the

technological convexity to properly exhibit weak disposability of desirable and undesirable outputs of city? (2) How to represent the technology heterogeneity between cities? (3) How can a city with inefficient EREC efficiency be improved? In order to answer these questions, we propose a comprehensive method for evaluating the cities' EREC performance using DDF and meta-frontier models. The proposed models consider the intrinsic differences between cities at the technical level. The potential improvement sources for EREC performance are also broken down into layers and then analyzed. Subsequently, the proposed models are applied to assess the EREC performance of 211 Chinese cities.

The main theoretical contributions of this paper are as follows. First, this paper proposes an improved DEA model to model a convex technology properly and exhibit weak disposability of desirable and undesirable outputs. Second, the improved DEA model is further extended to two EREC models by group- and meta-frontier, respectively. Third, a new TGR index is proposed to effectively solve the problem of TGR exceeding unity.[1] Fourth, the total latent improvement capacity is decomposed into management potential capacity and technology potential capacity by considering the management and technology heterogeneity. The proposed models are used for evaluating EREC performance of 211 Chinese cities.

Apart from the theoretical contributions, we also derive some new and interesting results as follows: First, our proposed models can properly evaluate the cities' efficiency, and the results show that Chinese cities still have a significant potential for EREC. Second, different from the previous studies (e.g. Wang et al., 2014; Lin and Zhao, 2016), the central area has the lowest EREC efficiency because more heavily polluting industries have been transferred into the central area from the eastern area recently. Third, the northeastern region is at the most inferior technology level (differing from studies of Wang et al., 2013 and Wang et al., 2014) since the traditional heavy industries and deteriorating economy have hindered technology development of the northeastern region. Fourth, managerial and technical factors are the two main sources for the loss of EREC efficiency in Chinese cities. We also provide some feasible suggestions for improving the EREC efficiency of Chinese cities. In sum, our proposed models can not only measure the city performance properly, but also contribute to the theory and application of DEA and EREC.

The remainder of this paper is organized as follows. In Section 2, the preliminary DEA-based EREC models are investigated, and the comprehensive models combining the DDF and the meta-frontier method are proposed. Section 3 presents an empirical research of 211 cities in China mainland. Section 4 discusses the potential sources and strategies to improve EREC efficiency. Section 5 concludes the paper.

2. Methodology

The model proposed in this paper employs the DDF technique. Therefore, this section firstly presents the DDF-DEA methods in Section 2.1. In subsequent, the two non-radial DEA models are proposed in Section 2.2 and 2.3, respectively.

2.1. Traditional DDF-DEA model

In general, the traditional DEA models are constructed based on the Shephard distance function technique. Through the traditional DEA models, the desirable and undesirable outputs are expanded following the same proportion (Zhang and Choi, 2014). This technique leads to that it is not credited to reduce the undesirable output (Lin and Du, 2015). Aiming at this problem, Chung et al. (1997) suggested introducing the DDF into the DEA model, given that DDF can effectively distinguish the weak and strong disposability existing between outputs (e.g. desirable and undesirable outputs). The DDF-DEA model also permits to increase the desirable output and simultaneously reduce the inputs and undesirable output. Owing to such advantages, the DDF-DEA model has become a popular method in empirical studies (e.g., Färe et al., 2007; Riccardi et al., 2012; Molinos-Senante et al., 2016).

This paper supposes that each city consumes the energy and non-energy inputs to produce the desirable outputs, simultaneously accompanied by the desirable outputs. The energy input is denoted as ${}^{E}X$ $(j = 1, \ldots, J)$, the non-energy input is denoted as ${}^{NE}X$ $(k = 1, \ldots K)$, the desirable output is denoted as ${}^{D}Y$ $(p = 1, \ldots, P)$, and the undesirable output is denoted as ${}^{UD}Y$ $(q = 1, \ldots, Q)$. This study primarily aims to investigate EREC in the cities. The specific focus is on efficiency evaluation and latent improvement capacity analysis. Therefore, the vector of adjustment for inputs and outputs is $g = (-g_{E_X}, 0, g_{D_Y}, -g_{UD_Y})$. In terms of the assumption of variable returns to scale (Wang and Wei, 2014; Picazo et al., 2012), Wang et al. (2015b) used a linear DEA Model (1) to determine the latent improvement capacity of EREC performance strategies.

$$
\begin{aligned}
&\vec{D} = \max\ \beta_o \\
&s.t. \sum_{z=1}^{N} \lambda_z {}^{E}X^{j} \le {}^{E}X_o^{j} - \beta_o {}^{E}X_o^{j}, \quad j = 1, \ldots, J, \\
&\sum_{z=1}^{N} \lambda_z {}^{NE}X^{k} \le {}^{NE}X_o^{k}, \quad k = 1, \ldots, K, \\
&\sum_{z=1}^{N} \lambda_z {}^{D}Y^{p} \ge {}^{D}Y_o^{p} + \beta_o {}^{D}Y_o^{p}, \quad p = 1, \ldots, P, \\
&\sum_{z=1}^{N} \lambda_z {}^{UD}Y^{q} = {}^{UD}Y_o^{q} - \beta_o {}^{UD}Y_o^{q}, \quad q = 1, \ldots, Q, \\
&\sum_{z=1}^{N} \lambda_z = 1, \quad z = 1, \cdots, N, \\
&\lambda_z \ge 0.
\end{aligned}
\tag{1}
$$

In Model (1), N is the amount of the evaluated cities and λ_z is the weight. Moreover, β_o is the ratio of energy conservation (energy-conservation improvement capacity) and the reduction in undesirable outputs (the emission reduction latent capacity). For the oth city, the EREC efficiency can be defined as

$$GEE_o = 1 - \beta_o. \tag{2}$$

In Model (1), the contracted rate of inputs and undesirable outputs is assumed to be equal to the expanded rate of desirable outputs. Thus, Model (1) is treated as a radial measure of efficiency. From an axiomatic approach, radial measure is probably more acceptable because of the desirable mathematical characteristics of the efficiency function (Sahoo et al., 2011). However, Fukuyama and Weber (2009) emphasized the existence of non-zero slacks in the process of efficiency evaluation, and radial efficiency measures may overestimate efficiency.

[1] As indicated by Wang et al. (2016), the TGR construction should obey the principle of common but differentiated responsibilities (CBDR). CBDR principle was proposed by *Kyoto Protocol* in 1997. Based on the CBDR principle, all TGR scores should be between zero and one. If TGR is larger than unity, it is useless.

2.2. Proposed group frontier DEA model

As discussed in Section 2.1, the DDF-DEA model uses the same proportion to augment the desirable output and contract the undesirable output/inputs. As such, the radial measure method may overestimate the efficiency for the evaluated unit (Du et al., 2014). To solve this issue, this section proposes a new DEA model for EREC by the non-radial measure based on the DDF and meta-frontier methods. Compared with the non-radial DDF-DEA models proposed by Zhou et al. (2012), Zhang et al. (2013), and Zhang and Choi (2013), our proposed model in this paper can effectively deal with convex constraint functions.

Assuming that G technology sets (sub-groups) exist among all cities, the gth group-specific DDFs can be defined as follows:

$$\overrightarrow{D}^{g}\left({}^{E}X^{j}, {}^{NE}X^{k}, {}^{D}Y^{p}, {}^{UD}Y^{q}\right) = \sup\Big\{w^{T}\beta : \left({}^{E}X^{j}, {}^{NE}X^{k}, {}^{D}Y^{p}, {}^{UD}Y^{q}\right) + diag(\beta)^{*}g \in T^{g}\Big\} \tag{3}$$

where $\beta = (\beta_o^j, \beta_o^k, \beta_o^p, \beta_o^q)$and $g = (-g_E, 0, g_D, -g_{UD})$. The following is a possible representation of the efficiency measure of DMU_o using the group-specific technology and assuming variable returns to scale:

$$\min\ \beta_o^g = \frac{\frac{1}{2}\left[\left(1-\frac{1}{J}\sum_{j=1}^{J}\beta_o^j\right)+\left(1-\frac{1}{Q}\sum_{q=1}^{Q}\beta_o^q\right)\right]}{1+\frac{1}{P}\sum_{p=1}^{P}\beta_o^p}$$

$$s.t.\sum_{z=1}^{N^g}\left(\lambda_z^g+u_z^g\right){}^{E}X^{j} \le {}^{E}X_o^j - \beta_o^j\,{}^{E}X_o^j, \quad j=1,\ldots,J,$$

$$\sum_{z=1}^{N^g}\left(\lambda_z^g+u_z^g\right){}^{NE}X^{k} \le {}^{NE}X_o^k, \quad k=1,\ldots,K,$$

$$\sum_{z=1}^{N^g}\lambda_z^g\,{}^{D}Y^{p} \ge {}^{D}Y_o^p + \beta_o^p\,{}^{D}Y_o^p, \quad p=1,\ldots,P, \tag{4}$$

$$\sum_{z=1}^{N^g}\lambda_z^g\,{}^{UD}Y^{q} = {}^{UD}Y_o^q - \beta_o^q\,{}^{UD}Y_o^q, \quad q=1,\ldots,Q,$$

$$\sum_{z=1}^{N^g}\left(\lambda_z^g+u_z^g\right)=1, \quad z=1,\cdots,N^g,$$

$$\lambda_z^g, u_z^g \ge 0.$$

In Model (4), N^g is the number of evaluated DMUs in the gth specific-group.λ_z^g and μ_z^g are the weightings. β_o^j is the energy conservation proportion (energy-conservation improvement capacity). β_o^p is the desirable output increase ratio. β_o^q is the reduction proportion for ${}^{UD}Y_o^q$ (the emission reduction improvement capacity). β_o^g is the efficiency score of DMU_o in the gth specific-group. Model (4) is also based on non-radial DDF, but it allows for possible contraction and non-proportional expansion of inputs and outputs. The model includes the important properties of DDF described in Färe and Grosskopf (2005). Owning to the variable returns to scale technology, Kuosmanen (2005) likewise pointed out that exclusively imposing the constraint $\sum\lambda_n^g = 1$ is not sufficient to model a convex technology and exhibit the weak disposability among the desirable and undesirable outputs. Therefore, the present paper introduced an added weighting u_n^g in Model (4) based on Kuosmanen (2005).

Model (4) is a nonlinear program, and difficult to be solved. It can be transformed into the following linear program by introducing a variable t ($t > 0$). The transformation steps are as follows:

Step 1: Set $\frac{1}{1+\frac{1}{P}\sum_{p=1}^{P}\beta_o^p} = t$. Model (4) can be changed into Model (5).

$$\min\ \beta_o^g = t - \frac{t}{2J}\sum_{j=1}^{J}\beta_o^j - \frac{t}{2Q}\sum_{q=1}^{Q}\beta_o^q$$

$$s.t.1+\frac{1}{P}\sum_{p=1}^{P}\beta_o^p = \frac{1}{t}$$

$$\sum_{z=1}^{N^g}\left(\lambda_z^g+u_z^g\right){}^{E}X^{j} \le {}^{E}X_o^j - \beta_o^j\,{}^{E}X_o^j, \quad j=1,\ldots,J,$$

$$\sum_{z=1}^{N^g}\left(\lambda_z^g+u_z^g\right){}^{NE}X^{k} \le {}^{NE}X_o^k, \quad k=1,\ldots,K,$$

$$\sum_{z=1}^{N^g}\lambda_z^g\,{}^{D}Y^{p} \ge {}^{D}Y_o^p + \beta_o^p\,{}^{D}Y_o^p, \quad p=1,\ldots,P, \tag{5}$$

$$\sum_{z=1}^{N^g}\lambda_z^g\,{}^{UD}Y = {}^{UD}Y - \beta_o^q\,{}^{UD}Y, \quad q=1,\ldots,Q,$$

$$\sum_{z=1}^{N^g}\left(\lambda_z^g+u_z^g\right)=1, \quad z=1,\cdots,N^g,$$

$$\lambda_z^g, u_z^g \ge 0.$$

Step 2: Let $\overline{\beta}_o^p = t\beta_o^p$, $\overline{\beta}_o^j = t\beta_o^j$,$\overline{\beta}_o^q = t\beta_o^q$,$\overline{\lambda}_z^g = t\lambda_z^g$ and $\overline{u}_z^g = tu_z^g$. Model (5) can be changed into Model (6).

$$\min\ \beta_o^g = t - \frac{1}{2J}\sum_{j=1}^{J}\overline{\beta}_o^j - \frac{1}{2Q}\sum_{q=1}^{Q}\overline{\beta}_o^q$$

$$s.t.t+\frac{1}{P}\sum_{p=1}^{P}\overline{\beta}_o^p = 1$$

$$\sum_{z=1}^{N^g}\left(\overline{\lambda}_z^g+\overline{u}_z^g\right){}^{E}X^{j} \le t\,{}^{E}X_o^j - \overline{\beta}_o^j\,{}^{E}X_o^j, \quad j=1,\ldots,J,$$

$$\sum_{z=1}^{N^g}\left(\overline{\lambda}_z^g+\overline{u}_z^g\right){}^{NE}X^{k} \le t\,{}^{NE}X_o^k, \quad k=1,\ldots,K, \tag{6}$$

$$\sum_{z=1}^{N^g}\overline{\lambda}_z^g\,{}^{D}Y^{p} \ge t\,{}^{D}Y_o^p + \overline{\beta}_o^p\,{}^{D}Y_o^p, \quad p=1,\ldots,P,$$

$$\sum_{z=1}^{N^g}\overline{\lambda}_z^g\,{}^{UD}Y^{q} = t\,{}^{UD}Y_o^q - \overline{\beta}_o^q\,{}^{UD}Y_o^q, \quad q=1,\ldots,Q,$$

$$\sum_{z=1}^{N^g}\left(\overline{\lambda}_z^g+\overline{u}_z^g\right)=t, \quad z=1,\cdots,N^g,$$

$$\overline{\lambda}_z^g, \overline{u}_z^g \ge 0.$$

Step 3: The optimal solution of Model (6) is denoted as $(t^*, \overline{\beta}_o^{*j}, \overline{\beta}_o^{*p}, \overline{\beta}_o^{*q}, \overline{\lambda}_z^{g*}, \overline{u}_z^{g*})$; then, the optimal solution of Model (4) can be obtained through

$$\beta_o^j = \frac{\overline{\beta}_o^{*j}}{t^*}, \beta_o^p = \frac{\overline{\beta}_o^{*p}}{t^*}, \beta_o^q = \frac{\overline{\beta}_o^{*q}}{t^*}, \lambda_z^g = \frac{\overline{\lambda}_z^{g*}}{t^*}, u_z = \frac{\overline{u}_z^{g*}}{t^*}. \tag{7}$$

Definition 1. For DMU_o, β_o^g is the efficiency score in the gth specific-group. Therefore, the latent improvement capacity of DMU_oin the gth specific-group (LICG) is

$$LICG_o = 1 - \beta_o^g. \tag{8}$$

2.3. Proposed meta-frontier DEA model

Model (4) assumes that all the cities evaluated have similar and consistently applied production technologies. However, numerous cities in China are diverse in a number of ways, and technology gaps between them clearly exist. That is to say, technology among cities in China is heterogeneous. To measure EREC efficiency with heterogeneous technology, the meta-frontier was used to extend Model (4). Through the extended models, all cities are divided into G types of groups $(G>1)$ based on the heterogeneous technology. The amount of city group g is N^g; then, we have$\sum_{g=1}^{G} N^g = N$. The DMUs of the gth group have similar production technology levels, and these cities form a frontier group. The production frontier using the meta-frontier method is obtained by collating the production frontiers of all G groups. That is, the production frontier of the meta-frontier method is formed by considering all cities. AssumingT^m is the production possibility set of the meta-frontier, and T^g is the production possibility set of the group frontier. For any group j, if $({}^E X^j, {}^{NE}X^k, {}^D Y^p, {}^{UD}Y^q) \in T^g$, then $({}^E X^j, {}^{NE}X^k, {}^D Y^p, {}^{UD}Y^q) \in T^m$. If $({}^E X^j, {}^{NE}X^k, {}^D Y^p, {}^{UD}Y^q) \in T^m$, then this input–output combination must belong to a group, and $T^m = \{T^1 \cup T^2 \cup \cdots \cup T^G\}$.

Under the meta-frontier, the performance of energy saving and emission reductions is described as Model (9) and Eq. (11), respectively.

$$\min\ \beta_o^m = \frac{\frac{1}{2}\left[\left(1 - \frac{1}{J}\sum_{j=1}^{J}\beta_o^j\right) + \left(1 - \frac{1}{Q}\sum_{q=1}^{Q}\beta_o^q\right)\right]}{1 + \frac{1}{P}\sum_{p=1}^{P}\beta_o^p}$$

$$\begin{aligned}
&s.t. \sum_{g=1}^{G}\sum_{z=1}^{N^g}(\lambda_z^m + u_z^m) \le {}^E X_o^j - \beta_o^j {}^E X_o^j, \quad j = 1, \ldots, J,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}(\lambda_z^m + u_z^m){}^{NE}X^k \le {}^{NE}X_o^k, \quad k = 1, \ldots, K,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}\lambda_z^m {}^D Y^p \ge {}^D Y_o^p + \beta_o^p {}^D Y_o^p, \quad p = 1, \ldots, P,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}\lambda_z^m {}^{UD}Y^q = {}^{UD}Y_o^q - \beta_o^q {}^{UD}Y_o^q, \quad q = 1, \ldots, Q,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}(\lambda_z^m + u_z^m) = 1, \quad z = 1, \cdots, N^g,\\
&\lambda_z^m, u_z^m \ge 0.
\end{aligned} \tag{9}$$

In Model (9), λ_z^m and μ_z^m are the weightings, andβ_o^m is the EREC efficiency of the oth city. Model (9) is a non-linear program that can be transformed by following the above three steps.

$$\begin{aligned}
&\min \beta_o^m = t - \frac{1}{2J}\sum_{j=1}^{J}\overline{\beta}_o^j - \frac{1}{2Q}\sum_{q=1}^{Q}\overline{\beta}_o^q\\
&s.t.\ \ t + \frac{1}{P}\sum_{p=1}^{P}\overline{\beta}_o^p = 1\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}\left(\overline{\lambda}_z^m + \overline{u}_z^m\right){}^E X^j \le t\,{}^E X_o^j - \overline{\beta}_o^j {}^E X_o^j, \quad j = 1, \ldots, J,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}\left(\overline{\lambda}_z^m + \overline{u}_z^m\right){}^{NE}X^k \le t\,{}^{NE}X_o^k, \quad k = 1, \ldots, K,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}\overline{\lambda}_z^m {}^D Y \ge t\,{}^D Y_o^p + \overline{\beta}_o^p {}^D Y_o^p, \quad p = 1, \ldots, P,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}\overline{\lambda}_z^m {}^{UD}Y = t\,{}^{UD}Y_o^q - \overline{\beta}_o^q {}^{UD}Y_o^q, \quad q = 1, \ldots, Q,\\
&\sum_{g=1}^{G}\sum_{z=1}^{N^g}\left(\overline{\lambda}_z^m + \overline{u}_z^m\right) = t, z = 1, \cdots, N^g,\\
&\overline{\lambda}_z^m, \overline{u}_z^m \ge 0
\end{aligned} \tag{10}$$

Definition 2. ForDMU_o, β_o^m is the efficiency score in the meta-frontier. Therefore, the latent improvement capacity of DMU_o in the meta-frontier (LICM) is defined as

$$LICM_o = 1 - \beta_o^m. \tag{11}$$

If the $LICM_o$ is equal to 0, then the city o is efficient in the meta-technology set. Or else, the efficiency $0 \le LICM_o < 1$, then city o is inefficient.

2.4. Breakdown of the latent capacity

As aforementioned, Model (4) is based on the group frontier, while Model (9) is based on the meta-frontier. This section will discuss how to breakdown the meta-frontier inefficiency obtained by Model (9) into technology inefficiency (i.e., technology potential) and management inefficiency (i.e., management potential) based on the group frontier inefficiency derived by Model (4).

A comparison of Models (4) and (9) reveals that the latter has more reference units. Therefore, the production frontier of Model (9) must represent the best production technology (Zhang et al., 2013; Oh, 2010). In Model (4), the production frontier only represents the technological level of the g group. Therefore, the EREC efficiency obtained by the meta-frontier will constantly be less than the performance of the group frontier; that is, $\beta_o^m \le \beta_o^g$. This phenomenon is explained as follows: different production technology references lead to different performance results.

To identify the of technology heterogeneity for each city group, a EREC technology gap ratio index (TGR) is constructed according to Battese et al. (2004), as shown in the following equation:

$$TGR_o = \beta_o^m / \beta_o^g. \tag{12}$$

In Eq. (12),$0 < TGR_o \le 1$, if $TGR_o$is closer to 1, the technology heterogeneity is smaller. In other words, the efficiency of the

group's frontier is closer to the efficiency of the meta-frontier. Otherwise, if TGR_o is closer to 0, the technology heterogeneity is greater.

Based on Chiu et al. (2012) and Lin and Du (2013), a city's total latent improvement capacity (TLIC) for EREC can be further broken down into two parts, namely, management potential (MP) and technological potential (TP), as shown in Eqs. (13) and (14) respectively.

Definition 3. For DMU_o, the management potential (MP) can be described as follows:

$$MP_o = LICG_o = 1 - \beta_o^g. \tag{13}$$

From Model (4), we know that the envelopment frontier is obtained by the DMUs in the same group. DMUs in the same group have similar production techniques, so the reason for inefficiency of DMU_o is poor management. Then the distance from DMU_o to group envelopment frontier is defined as MP.

Definition 4. For DMU_o, the technological potential (TP) can be described as follows.

$$TP_o = LICM_o - LICG_o = (1 - TGR_o)LICG_o = \left(1 - \beta_o^m\right) - \left(1 - \beta_o^g\right) = \beta_o^g - \beta_o^m \tag{14}$$

From Model (9), we know that the envelopment frontier is obtained by all groups' DMUs. That is, the envelopment frontier of Model (9) is enveloped by all group envelopment frontiers. If DMU_o attempts to become efficient through the meta-frontier, it needs to pass two steps. In the first step, DMU_o should reach the group frontier (that is MP). In the second step, DMU_o should reach the meta-frontier from the group frontier. The gap between the group frontier and the meta-frontier lies mainly in the technology gap. Thus the distance for DMU_o from group frontier to meta-frontier is defined as TP.

Definition 5. For DMU_o, total latent improvement capacity (TLIC) for EREC can be described as follows.

$$TLIC_o = TP_o + MP_o = 1 - \beta_o^m. \tag{15}$$

In fact, TLIC is the distance from DMU_o to the meta-frontier. Based on the definitions 3 and 4, the TLIC is broken down into MP and TP.

From Eq. (14), the TP of EREC efficiency is clearly generated by the difference between the group frontier and the meta-frontier. Specifically, the TP of a city can be obtained by calculating the distance between its projections on the group frontier and the meta-frontier. If a city's $MP > TP$, focus must be made on making improvements to the current underperforming management rather than on the technical levels.

3. Empirical research

3.1. Data collection

In this section, we utilize the proposed models in Section 3 to analyze EREC efficiency in mainland China's cities. China possesses vast territories and abundant resources. Any future urban development and management will be significantly influenced by complex and volatile geographic factors, culture, and economic levels in the many different regions. In line with the most previous studies (Yang and Zhang, 2016; Chen and Jia, 2017; Zhu et al., 2017), this paper also adopts the conventional geographic regional division of China, thereby dividing the country into four geographic regions as listed in Table 1 below.

The data on energy saving, emissions, and economic development for Chinese cities was collected from the *2016 China City Statistical Yearbook*. In the *China City Statistical Yearbook*, not every city will disclose all the indicator data, e.g. coal consumption data. Based on the availability of data, we collected data from 211 Chinese cities. Eight indicators are used to analyze the EREC efficiency of the Chinese cities: (1) fixed assets investment (10^6 RMB per person), (2) number of employed population (in 10^4), (3) water consumption (in 10^3 tons per person), (4) coal consumption (10^3 tons per person), (5) gross domestic product (GDP, in 10^6 RMB per person), (6) waste water emission (in 10^3 tons per person), (7) SO_2 emissions (in 10^3 tons per person), and (8) dust emission (in 10^3 tons per person). Of these indicators, the first four are inputs, the fifth one is a desirable output, and the others represent undesirable outputs.

3.2. Difference analysis of EREC efficiency

The efficiency and latent improvement capacity for all 211 cities were computed using Models (9) and (11) respectively. The average EREC efficiency of all cities is less than 1 at 0.613, which indicates a less than satisfactory performance. This finding suggests that the cities' rapid development has consumed excessive energy and emitted high levels of contaminants. On the basis of the EREC efficiency, Chinese cities can potentially improve at an overall rate of 38.7% (1−0.613 = 0.387). The efficiency of central cities is lowest at 0.4948 and significantly lower than the average Chinese city's efficiency value of 0.613. Models (4) and (9) were used to calculate the EREC efficiency for each city group through the meta-frontier and group frontier methods. Table 2 presents the statistics for EREC efficiency for each area.

Results from comparing the efficiencies obtained using the group frontier and meta-frontier methods suggest that the EREC efficiency of cities are different when different reference objects are selected; thus, we have $\beta_o^m \leq \beta_o^g$. The efficiencies of cities in the central, western and northeast regions show large increases under group frontier. Fig. 1 shows the amount of cities in the meta-production frontier (meta-efficiency is 1) and the group production frontier (group-efficiency is equal to 1). Numerous group-efficient cities are no longer efficient under the meta-frontier method. The reduced numbers of the eastern, central, western, and northeastern cities are 8, 17, 9, and 7, respectively.

The production technology of the meta-frontier includes all reference objects. Thus, EREC efficiency is lower than the group frontier efficiency. This finding is in agreement with the theoretical analysis outlined in Section 2. With the group frontier, the EREC efficiency can be used to analyze the latent improvement capacity for resource conservation and emission reduction for each city under existing technological conditions. The efficiency using the meta-frontier method can be used to examine all cities' latent improvement capacity based on the best levels.

Further investigating the differences in EREC efficiency obtained by the two methods requires using the Mann-Whitney method (a non-parametric statistical method) (Zhang et al., 2013). The null hypothesis of statistical method is that the distributions of two types of efficiency are the same. The results shown in Table 3 indicate that the efficiency in all areas (except the west) using different frontiers rejected the null hypothesis at the 10% significance level (P value of these areas <0.1). In other words, most cities utilizing a different reference frontier will obtain a significantly different efficiency rating. This finding shows that whether or not a city achieves better energy-saving and emission-reduction efficiency depends mainly on what is selected for comparison. In

Table 1
Division of the geographical regions of China.

Area	Provinces	Number of Cities
East	Beijing, Jiangsu, Shanghai, Guangdong, Zhejiang, Tianjin, Hebei, Shandong, Fujian	74
Central	Shanxi, Anhui, Hunan, Henan, Jiangxi, Hubei	70
West	Ningxia, Guangxi, Guizhou, Qinghai, Yunan, Gansu, Shanxi, Sichuan, Inner Mongolia, Chongqing, Shaanxi, Xinjiang	51
Northeast	Liaoning, Jilin, Heilongjiang	16

Table 2
Statistical descriptions of EREC efficiency for each area.

Area	Meta-frontier (MEE)				Group frontier (GEE)			
	Max	Min	Mean	Std. dev.	Max	Min	Mean	Std. dev.
East	1.0000	0.2130	0.6414	0.2457	1.0000	0.2353	0.7420	0.2285
Central	1.0000	0.2049	0.4948	0.2216	1.0000	0.2960	0.7349	0.2214
West	1.0000	0.3063	0.7099	0.2677	1.0000	0.3767	0.7922	0.2519
Northeast	1.0000	0.3302	0.6830	0.2675	1.0000	0.4008	0.9112	0.1885

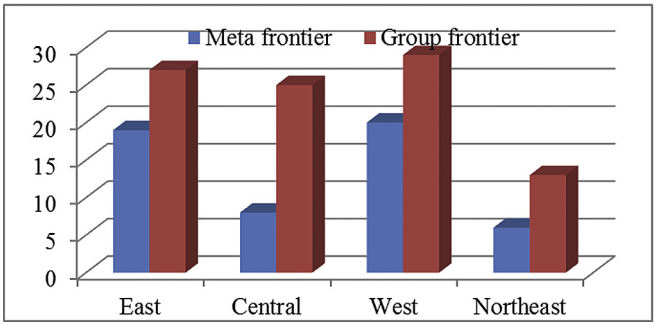

Fig. 1. Amount of cities in the two production frontiers.

addition, the potential improvement in a city's efficiency can be shown at multiple levels. For example, most cities in China today should take steps to strengthen environmental protection rather than focus on expanding the city. From a long-term development perspective, cities should constantly upgrade the equipment and techniques necessary to achieve optimal technology.

As shown in Table 3, the efficiency in the west for different frontiers significantly accepts the null hypothesis (P value of the East areas = 0.111). There are two main reasons. Xu and Ren (2017) indicates that the western provinces have strictly implemented EREC policies and optimized the industrial structure in recent years, leading to the improvement of energy utilization efficiency. In addition, we calculate the average emissions of four regions in the last two years (The data is collected from *2015 China Statistical Yearbook and 2016 China Statistical Yearbook*). Compared with 2015, the SO_2 and dust emissions in the western region in 2016 declined by 7.39% and 16.72%, respectively. Compared with other regions, the decline of SO_2 and dust emissions in the western region is the most significant. These two reasons explain why the western region achieves higher meta-frontier EREC efficiency.

To measure the degree of technology gap between different city areas, the TGR of each city was calculated using Eq. (12). It is noted that all TGRs are not more than the unity. Then the Kruskal–Wallis method is used under condition that the four areas are independent, and the result is shown in Table 4. The Kruskal–Wallis result rejects the null hypothesis ($P < 0.01$), which means that the TGR of cities across the fourareas is statistically and significantly different. Figs. 2 and 3 show four stair-step shape distributions of the TGR of the four areas. From Figs. 2 and 3, we find that the TGR scores in the eastern and western cities is more than 0.86 (Higher than the national average). The TGRs of the central and northeastern cities, lower than the national average of 0.798, are also less developed than that of the eastern cities. TGR reflects the technological heterogeneity between cities. Taking the central area as an example, the average efficiency of cities in central area using meta-frontier is 0.4948. This shows that the efficiency improvement potential of central cities reaches 50.52% under the national optimal technology standards. However, under the optimal technology standards of the central region, the efficiency improvement potential of central cities is 26.51%. The main reasons for the differences of the two efficiencies in the central region is that there are differences in technology reference standards. This explains why the TGR value in the central region is relatively large. Similar to the central region, the optimal technology level in northeastern region is lower than the national best technical level.

4. Discussion on potential sources

On the basis of the EREC efficiency analysis of these cities, we further discuss and analyze the sources of efficiency loss for facilitating both EREC policy. Using Eqs. (13)–(15), Fig. 4 shows the division of the potential improvements of the four areas' cities into technical potential and management potential.

As illustrated above, managerial and technical factors are the two main sources of loss of efficiency in Chinese cities. The proportions are 60.75% and 39.25%, respectively. The eastern region has a leading position in technology, whereas over half of the EREC

Table 3
Mann-Whitney test results for EREC efficiency.

Area	Null hypothesis	U statistic score	Z statistic score	*P* score
East	The distributions of two types of efficiency are the same.	2070.50	−2.58	0.010
Central		980.00	−6.14	0.000
West		1068.50	−1.59	0.111
Northeast		74.50	−2.50	0.012

Table 4
Kruskal–Wallis test result of TRG.

Null hypothesis	Kruskal–Wallis H statistics score	P score
The four distributions have the same center position	48.853	0.000

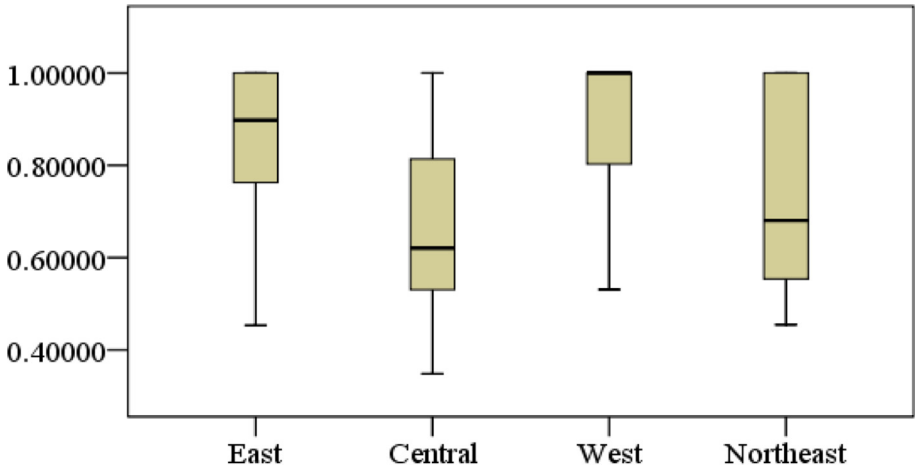

Fig. 2. Quartile of each group's TGR.

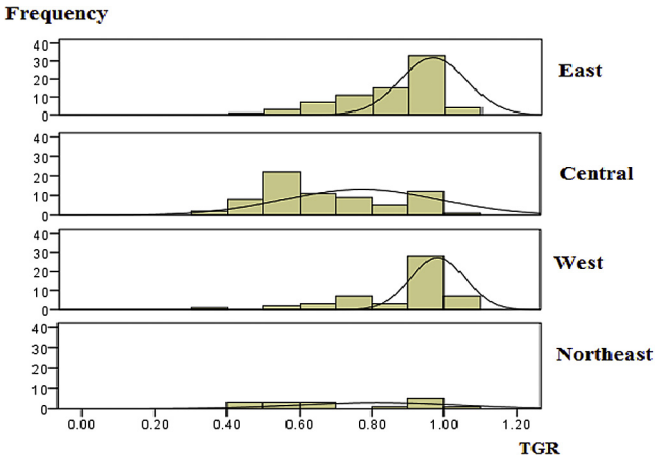

Fig. 3. Frequency of each group's TGR.

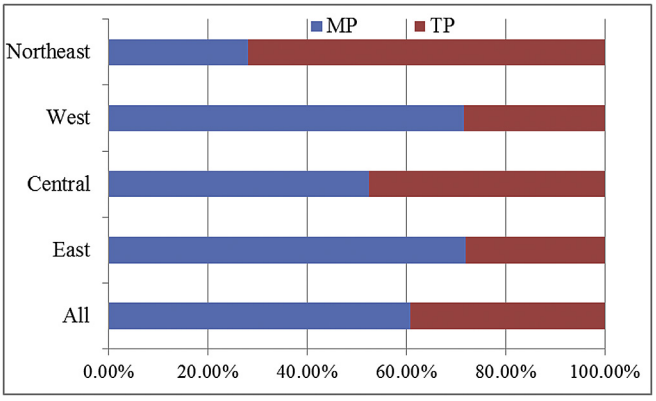

Fig. 4. Potential sources of EREC efficiency.

potential in the Northeast region results from the technology gap. This finding indicates that narrowing the gap between regions is highly significant to the EREC of China.

Many Chinese cities urgently require improving their EREC efficiency from the perspective of management factors, although these cities currently exert huge efforts to their update EREC technologies. For example, in eastern and west cities, the ratio (e.g. MP/TP) is higher than 50%. In eastern cities, the loss of EREC efficiency because of invalid management is approximately 71.95%. Thus, how to improve management level should be the main emphasis for EREC in these cities.

Different regions require different standards for energy conservation and emission reduction. To illustrate, the level of technology in the northeast region is relatively low. Adopting the national meta-frontier standards is inappropriate for the Chinese government when making the EREC targets for the northeast region cities. When fully considering the actual level of technology in the northeast region, choosing the relatively comparable group frontier technology as a reference standard is appropriate for the Chinese government.

Cities in different areas should improve their EREC efficiency based on their own circumstances. In order to provide the specific suggestion for improving efficiency, the cities were categorized into four types based on potential sources (Fig. 5 and Table 5).

Type 1 has 43 cities, including 8 eastern, 29 central, 3 western, and 3 northeastern cities, where the technology and management potential are both higher than the mean values. To improve EREC efficiency, these cities should pay attention to both the managerial and technical factors with regard to energy saving and emission reduction.

Type 2 has 41 cities, including 8 eastern, 17 central, 10 western, and 6 northeastern cities, where each city should focus on improving in the area of technology. These cities should all focus on updating and improving their technological capacity and equipment. These improvements could take the form of importing advanced green production technologies and actively seeking technical assistance. Such steps would assist in achieving improvements in EREC efficiency by narrowing the existing

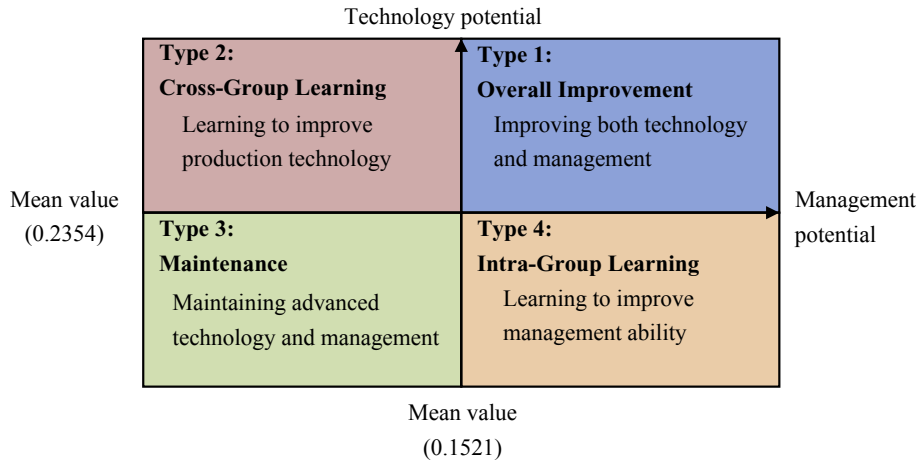

Fig. 5. Strategy matrix to improve EREC efficiency.

Table 5
Number of cities belonging to four types.

	Total	Eastern cities	Central cities	Western cities	Northeastern cities
Type 1	43	8	29	3	3
Type 2	41	8	17	10	6
Type 3	59	24	9	20	6
Type 4	68	34	15	18	1

technology gap.

Type 3 has 59 cities, including 24 eastern, 9 central, 20 western, and 6 northeastern cities, where both the technology and management potential are lower than the mean values. On the one hand, cities of Type 3 should consolidate their current technology level and management capability. On the other hand, they should help cities in other categories through exporting technology and sharing management experience. In such ways, the effect of technology spillover can be enhanced positively, and the progress of green technologies can be facilitated.

Type 4 has 68 cities, including 34 eastern, 15 central, 18 western, and 1 northeastern cities, where each city should focus on improving in terms of management capacity in relation to energy saving and pollution control. Such improvements could take the form of learning from and imitating advanced management systems, administration mode, and managerial experiences. These cities should give full play to the role of management factors in their efforts to improve emission reduction and environmental protection.

Technology gaps exist in different regions and even in different cities within the same region. Fig. 5 and Table 5 show the division of all Chinese cities into four types based on this actual situation. However, achieving the best technology level would be a long-term accumulation for all Chinese cities. In the short term, group emission reduction potential (management potential) can effectively play a role in energy saving and pollution control because group-frontier efficiencies reflect the cities' actual EREC levels in the same region. From a long-term perspective, narrowing the technology gap of EREC between regions can realize the sustainable development of the economy and the environment. To achieve this goal, technology spillover between regions is a feasible method. The coordinated development of all regions can aid in updating the technologies of EREC in each group, thereby promoting the overall efficiency of national EREC.

5. Conclusions and policy implications

As a sustainable development strategy, EREC have become extremely important in everyone's life and in national production. These approaches can save non-renewable energy and reduce waste emissions to lessen environmental destruction and improve environmental protection. As the main thrust of environmental emission control, the city's EREC work has increasingly become the focus of both the government and the academe. Production technologies between cities are currently heterogeneous because of the differences in the levels of economic development and geographical factors. Based on this finding, we proposed meta- and group-frontier non-radial DDF-DEA models. The proposed models were used to evaluate the EREC efficiency of 211 Chinese cities.

Through empirical study, we find that the average EREC efficiency of Chinese cities is 0.613, implying that Chinese cities have a significant potential to reduce emission and conserve energy. Second, the central area has the lowest EREC efficiency. The result is different from the studies of Wang et al. (2014) and Lin and Zhao (2016) where the EREC efficiency in Western China is the lowest. The reasons for this result includes that: (1) our study incorporates the latest year's data, reflecting the Chinese latest EREC situation; (2) more heavily polluting industries have been transferred into the central area from the eastern area in recent years, which accelerates economic developments but causes serious environmental issues in the central area (Wang et al., 2016). Third, the TGR results show that significant technology gaps exist between regions in China. In general, the technology level in the eastern region is the most advanced. However, the northeastern region is at the most inferior technology level. This finding is in sharp contrast with Wang et al. (2013, 2014), who documented that the EREC technology level in the western area is the worst. Recently the western region has rapidly developed clean energy (e.g. wind and solar energy) instead of traditional fossil fuel energy resources, and become the most efficient user of large-scale use of clean energy centers (Wu et al., 2015a, b). This has greatly improved the EREC technology level in

the western region. The northeastern region, a traditional industrial base, is heavily dependent on metallurgy, iron and steel, coal industries for economic development (Zhou et al., 2016). Sun et al. (2017) indicated that the economy of the northeastern Chinese area has deeply declined recently, and industrial added value above designated size has continued to grow negatively. Traditional heavy industries (e.g. industries with high energy consumption and high pollution) and deteriorating economy have negatively affected the EREC technology development. Finally, managerial and technical factors are the two main sources for the loss of EREC efficiency in Chinese cities, accounting for 60.75% and 39.25% respectively. Cities in different areas should improve their EREC efficiency based on their own circumstances.

Based on the above analysis, the major policy implications for Chinese cities can be summarized in three distinct areas. First, according to the efficiency obtained by meta-frontier, Chinese cities still possess significant potential for conserving energy and reducing emission. The results of potential sources (see Fig. 4) show that most cities in the eastern region have the advanced production technology. The reason is that the eastern region is the most economically developed area in China. With economic development, the production technology of the eastern region can keep pace with the international level. By contrast, the northeastern area has a backward production technology because there are a large number of heavy industries with extensive development in Northeast China (Zhou et al., 2016). Nevertheless, the economy in the northeast has being deteriorating recently (Sun et al., 2017). Therefore, we suggest that the local government should gradually abandon the extensive economic development mode, and adopt technological innovation to expedite economic development (National Development and Reform Commission, 2015). Otherwise, this economy-declining trend will not only result in a failure to accomplish the EREC tasks but also affect the economic development of these cities.

Second, due to the technology heterogeneity of EREC in Chinese cities, realizing technology convergence among cities is a long and arduous process. The feasible solutions for enhancing EREC efficiency would include improving the management ability and narrowing the technology gap. These two main approaches to improve efficiency can be regarded as short-term and long-term goals respectively. Thus, choosing the appropriate frontier as reference is highly essential for the inefficient city when evaluating potential EREC efficiency. Given that the technology gap cannot be eliminated in the short term, the environmental protection departments of the cities should gradually advance when formulating relevant EREC policies. For the short-term goal of Chinese cities, the group frontier representing the city's current estimate of the production technology can be used as a reference for improvement. That is, the inefficient cities should focus on improving their management ability. Once the short-term goal is effectively achieved, the meta-frontier representing the best technology can be used as a reference for technological improvement. In the context of the long-term goal for cities, narrowing the technology gap between different regions includes regional coordinated development and technology spillover. Such action can effectively improve China's overall performance in EREC.

Finally, China's overall energy-saving emission reduction targets cannot be achieved without the joint efforts of various regions. A huge difference exists between regions with respect to economic development, industrial structure, and resource endowment. These factors affect the efficiency of EREC in different regions. In general, the technology in the eastern region is mature. Meanwhile, the tasks of EREC in the central regions are difficult, and the technology gap is significant. Therefore, establishing a multilateral communication system for EREC between different regions is necessary. Through regular communication, sharing some new methods and experiences to improve resources utilization or reduce emissions is expected. Through the communication system, the technology cooperation for energy saving and emission reduction between regions can be possibly promoted in the following ways: developing diversified technology cooperation mechanisms, promoting new technology transformation among regions, and formulating technology support policies according to local conditions. Thus, establishing the above multilateral communication system will significantly improve the performance of EREC among regions.

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